Distributed Big Data Analytics
Efficient First Order Inductive Learner on Spark

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Problem Statement

Definition 1. A literal L may be predicate P or $\neg P$.
Definition 2. A clause body is a conjunction of literals.
Definition 3. A clause head is predicate.
Definition 4. A Horn clause consists of a head and a body:

$$P \leftarrow L_1, L_2, ..., L_n. \tag{1}$$

Definition 5. A learning rule for predicate P is a collection of Horn clauses each with head P.
The predicates can be defined *extensionally* as a list of tuples for which the predicate is true, or *intensionally* as a set of Horn clauses.
Definition 6. k-tuple $< a_1, a_2, \ldots, a_k >$ is a finite sequence of k constants.
Definition 7. A tuple satisfies a learning rule if it satisfies one of the Horn clauses of this rule.
For every relation a set of the $\oplus$tuples which belong to this relation is given. For a target relation a set of $\oplus$tuples is also given. A set of the $\ominus$tuples not belonging to the target relation may be given. The statement is introduced: if some tuple is not included in set $\oplus$tuples then it is $\ominus$tuple.

Problem statement: Using Spark framework realize FOIL to find a learning rule as a set of Horn clauses for the target relation that consistent with given positive examples and not cover any given negative examples.

Approach

Foil algorithm is realized using Scala in Spark framework.

1	Let Pred be the predicate to be learned
2	Let Pos be the positive examples
3	Until Pos is empty do:
4	Let Neg be the negative examples
5	Set Body to empty
6	Let Old be those variables used in Pred
7	CallLearnClauseBody
8	Add Pred ← Body to the rule
9	Remove from Pos all examples that satisfy the Body
7a	Procedure CallLearnClauseBody
7b	Until Neg is empty do:
7c	For each predicate-name P
7d	For each variabilization L of P
7e	Compute information gain of L and its negation
7f	Select literal L with most information gain
7g	Conjoin L to Body
7h	Add any new variables to Old
7i	Let Pos be all extensions of Pos that are satisfied by the literal
7j	Let Neg be all extensions of Neg that are satisfied by the literal

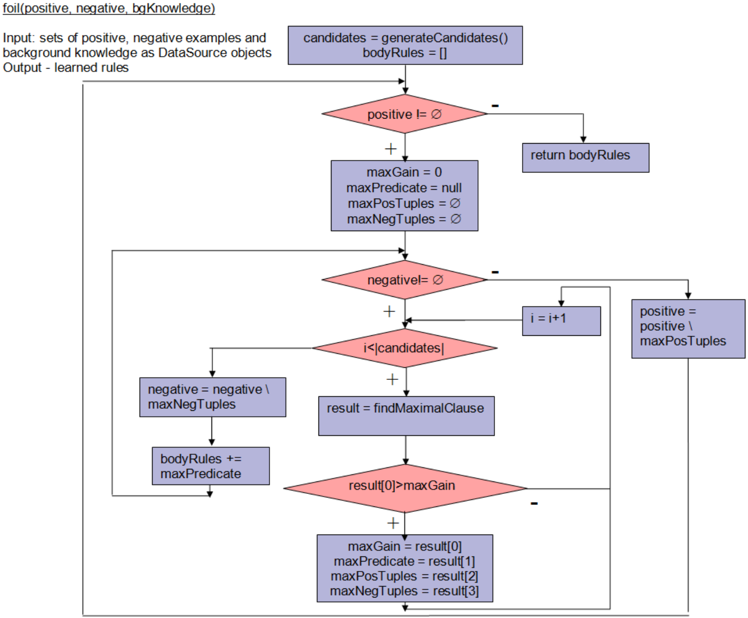
To select literal with greatest positive gain:

$$gain(L_i) = n_i^{\oplus\oplus} \cdot (I(T_i) - I(T_{i+1})), \quad I(T_i) = -\log_2(n_i^{\oplus}/(n_i^{\oplus} + n_i^{\ominus})), \quad (2)$$

$n_i^{\oplus}$ — a number of $\oplus$tuples in T_i, $n_i^{\ominus}$ — a number of $\ominus$tuples in T_i,

$n_i^{\oplus\oplus}$ — a number of the $\oplus$tuples in T_i represented by one or more tuples in T_{i+1}.

Implementation



Evaluation

Evaluation metrics: $\rho_k(A_1, A_2) = |n_k(A_1) - n_k(A_2)|$, $k = 1, 2, 3$.

Indicators: $n_1(A) = \frac{n^{\oplus}_{\mathrm{covered}}(A)}{n^{\oplus}_{\mathrm{given}}}$, $n_2(A) = \frac{n^{\ominus}_{\mathrm{covered}}(A)}{n^{\ominus}_{\mathrm{given}}}$, $n_3(A) = \mathrm{runtime}(A)$.

Experiment 1. (a), results: $daughter(X_1, X_2) \leftarrow female(X_1)parent(X_2, X_1)$; covered $\oplus$ examples: (Emily, Tom), (Mary, Ann); covered $\ominus$ examples: $\emptyset$.

Experiment 2. (b), results: $daughter(X_1, X_2) \leftarrow female(X_1)parent(X_2, X_1)$; covered $\oplus$ examples: (Opra, Ann), (Kate, Ann), (Lina, Kate), (Gail, Hovard); covered $\ominus$ examples: $\emptyset$.

Experiment 3. (b), results: $son(X_1, X_2) \leftarrow male(X_1)parent(X_2, X_1)$; covered $\oplus$ examples: (Ryan, Uve), (Bill, Opra), (Hovard, Ann), (Nick, Kate), (Uve, Ann), (Tom, Uve); covered $\ominus$ examples: $\emptyset$.

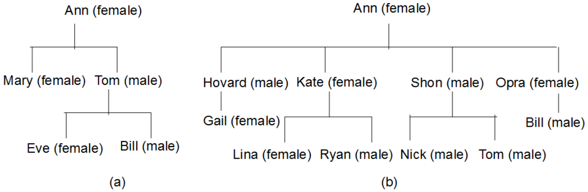


Table 2. Efficiency indicators.

No Experiment	Proportion of covered $\oplus$(%) examples	Proportion of covered $\ominus$ examples (%)	Running time (sec)
1	100	0	0.188
2	100	0	0.207
3	100	0	0.200

Conclusion and future work

Results of presented project are:

1. In Spark framework Foil algorithm is realized:

(i) the developed application gets the input data in extensionally form (i.e. consists of names and $\oplus$ and $\ominus$ tuples for target predicate, and names and $\oplus$ tuples for background predicates;)

(ii) the results are obtained both in intensionally form (i.e. as Horn clause for the target relation that consistent with given $\oplus$tuples and not cover any given $\ominus$tuples) and extensionally form.

2. To evaluate developed application the metrics based on three efficiency indicators are introduced.

3. three experiments were performed and on this base developed application is evaluated as having sufficient efficiency.

The future steps to developed application may be:

1. Carrying out experiments with a more complex data structure, for example, when a tree node is described by a large number of predicates;

2. Evaluation of the application efficiency compared to other implementations of the Foil algorithm.

Lesson learned

Besides the detailed study of the FOIL algorithm
we also consider as the results of this project the following:

1. The extension of our skills on applications development using the Spark framework and the Scala programming language;
2. The receive of the skills in evaluation of an applications effectiveness, including an experience in selection and drawing up of the training data.
3. The extension of our experience on writing of the reports and project drafting.

References

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